Evaluation of Transportation Level of Service Using Fuzzy Sets

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The literature on transportation level-of-service (LOS) evaluation indicates a strong impetus to move away from a strictly capacity/volume- or time/space-based measure to one that directly incorporates the perception of passengers. The difficulty has been that whereas such quantitative measures are reasonably simple to measure, other LOS attributes related to convenience and comfort are qualitative in nature. Such attributes obviously are better expressed in qualitative terms. A review of the literature indicates that suggested methodologies fail to incorporate directly passengers' service perceptions, as expressed in natural language. The use of fuzzy set theory, particularly linguistic fuzzy set models, as a technique for evaluating transportation LOSs is explored. An approach for evaluating airport passenger services using linguistic variables and fuzzy sets is presented. LOS is conceptualized as a hierarchical service system with subcomponents. An example of the model applied to an evaluation of airport terminal services is presented.

Although the evaluation presented in this paper can be applied to evaluate the level of service (LOS) of other modes of transport, the discussion centers on air transport, particularly airport service evaluation. Airport landside LOS evaluation has attained renewed interest in literature and is now recognized as an area needing urgent innovative research. This need is demonstrated in the FAA/TRB study on airport performance measures (*1*).

Measurement of system performance is important in assisting operational management with current airport system capacity, facilities, and services and for planning extra capacity. It has been noted that previous design standards established as measures of LOS and capacity took limited account of the balance between demand and supply. The methodology used is not transparent (i.e., no explicit indication is given on how LOS standards were derived). The wave of privatization and deregulation experienced within the aviation industry also has given a new impetus for competition among airports and a need for customer-oriented management of airport facilities and services. Continuous growth in demand must be met with both extra capacity, where necessary, and improved current standards of service. Achieving improved service management requires that other methods be established for LOS assessment and specification of standards; new methods must be developed that consider the cited limitations of current standards. The definition of user-based LOS is the quality and condition of service of a functional component or group of functional components as experienced by the users (*2*).

This paper concentrates on developing a methodology for establishing LOS measures based on users' perceptions. To develop this evaluation method, the paper first examines previous methods of transportation (i.e., LOS) evaluation, with particular reference to airport landside LOS. Research in other domains, particularly fuzzy concepts, is explored. It is noted that LOS from a user's point of view is a fuzzy concept that the individual can best describe verbally in imprecise terms only, even though planners prefer precise, quantifiable descriptions. This paper presents the necessary fuzzy set theory relevant to the proposed methodology, looks at an application of the methodology, and provides conclusions on the usefulness of the proposed method and areas for further research.

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REVIEW OF LOS EVALUATION METHODS

Previous literature contains only a few methods of LOS evaluation. The pre-1980 approach to LOS evaluation was based on establishing LOS standards for highway transport services, passenger terminals, and pedestrian walkways. These earlier standards defined LOS at a facility by area per person available at that facility at a given time (*3*). These standards are criticized for being based on either space-volume (i.e., space standards) or time-volume (i.e., time standards). Normally at a given facility, time and space interact, resulting in such LOS aspects as overcrowding.

The most important criticism of established standards is that they are unable to incorporate directly passengers' perceptions of LOS. Since the early 1980s, research on methods for evaluating LOS that incorporates passenger perception has gain renewed interest. User-based approaches for evaluating LOS, as identified in the literature, include a passenger perception response (P-R) model reported by Mumayiz and Ashford (*4*), a utility-based model reported by Omer and Khan (*5*), and models drawn from psychological scaling techniques reported by Mueller and Gosling (*6*) and Ndoh and Ashford (*7*). These approaches are also reviewed elsewhere (*7*). The cited approaches provide crisp scale values of LOS that cannot be given linguistic values that are precise in comparison with the manner in which passengers originally expressed their perceptions of services. In most instructions on surveys to identify users' perceptions of service, linguistic values typically are used. Common terms used to obtain LOS perception include *outstanding, good, acceptable, fair, and poor*. The quest for a method for evaluating passengers' perceptions of LOS is actually a quest for a way to best model the responses given by passengers in natural language. The methodology proposed in this paper provides such a framework for modeling linguistic variables using linguistic fuzzy set theory.

Other important background issues on LOS evaluation are identifying the important factors that determine LOS of any service system component and specifying an index of measure of the service level (*8*). Lemer (*1*) summarized the main LOS index measures, accounting for the views of passengers, airlines, government bodies, airport operators, and the community at large. Odoni and de Neufville recommend that passengers dwell times within the terminal be used as the basis for evaluating passenger perception of terminal LOS (*9*). Seneviratne and Martel found the following six factors to be determinants of LOS in the processing, holding, and waiting components of the airport: (a) information, (b) waiting time (for processing activities), (c) convenience (i.e., physical effort required for processing activities), (d) availability of seats, (e) concessions (i.e., variety and accessibility), and (f) internal environment (i.e., aesthetics and climate). The findings were drawn from a summer survey of departing passengers at Dorval International Airport in Montreal (*10*). Techniques for determining the importance rating of various LOS attributes can be improved using fuzzy set methods (*11,12*). The proposed evaluation method in this paper allows the direct incorporation of passenger perception of the importance of any service attribute within the evaluation scheme.

Elements of Fuzzy Set Theory

Fuzzy set theory was introduced by Zadeh (*13*) as a means of modeling ill-defined problems; since its inception, it has been applied in a wide variety of fields that need to deal with imprecise quantities (*14–17*). Fuzzy set theory is a generalization of ordinary set theory, providing an adequate conceptual framework and serving as a mathematical tool for analyzing practical problems that often are obscure, vague, or indistinct. This section summarizes some fundamental definitions and operations of fuzzy set theory that will be used in this paper. Further exposition on this subject can be found in other literature (*13,18*).

Linguistic Variables

It was noted previously that passengers often use qualitative terms to describe their perceptions of transportation LOS. The term "LOS" is considered a linguistic variable in this paper; a linguistic variable is defined as a variable, the values of which are words, phrases, or sentences, in a given language that can be either natural or artificial (*19*). For example, the overall LOS within the airport terminal can be considered a linguistic variable with meaningful natural language classification such as excellent, good, acceptable, poor, bad, or unacceptable. These words form a term set, or primary terms useful in defining passenger perception of LOS. The primary terms are themselves imprecise and can be qualified further using natural language qualifiers (or hedges), such as very, fairly, or highly, in order to provide more precise meaning to the perceived service quality. [The concept of hedges is very important and useful in linguistic variable computation. A hedge acts as a modifier of the primary term. For example, the hedge "very" intensifies the particular word with which it is used. Thus, if that hedge is applied to the linguistic value $A = low$ such that the value becomes "very low," it decreases the fuzziness of the elements of the linguistic value "low" by decreasing its membership grade. The intensification of A is expressed as INT(A). Other useful operations on linguistic variables include concentration, CON(A); dilation, DIL(A); normalization, NORM(A); fuzzification, SF(A,K); and shift on A and fuzzy set removal.]

Let X be a universe of discourse, or a set with elements x, where X is defined with respect to LOS evaluation, and let A be a subset of X. If each element, x, is associated with a membership value $\mu_A(x)$ within the subset A, then A is a fuzzy set. The membership grade is constrained in the interval [0,1]. Thus, in general, any subset A may be represented by m discrete values, $x_1, \ldots, x_m$, and m membership values, $\mu_A(x_m)$. That is,

$$A = [x_1 \mid \mu_A(x_1), x_2 \mid \mu_A(x_2), \ldots, x_m \mid \mu_A(x_m)] \tag{1a}$$

where = means "defined to be" and | is a delimiter.

The main computation of linguistic variables of interest here are fuzzy set addition, multiplication, division, min/max operations, and a measure of distance between fuzzy sets.

If A and B are two fuzzy subsets of the universes X and Y, with elements x and y, respectively, such that

$$A = [x \mid \mu_A(x), 1 \leq x \leq 9] \qquad \text{for all } x \text{ that belongs in } X \tag{1b}$$

and

$$B = [y \mid \mu_B(y), 1 \leq y \leq 9] \qquad \text{for all } y \text{ that belongs in } Y \tag{1c}$$

then fuzzy addition is defined as

$$\mu_{A+B}(z) = [\max \{\mu_A(x) \min \mu_B(y)\}] \tag{2a}$$

where

$$(x + y) = z$$

$$1 \leq z \leq 9$$

[Computationally, Equation 2a means that to calculate the degree of membership of z, in $A + B$, one must examine all possible ways that two elements (x, y) can sum to z and examine the degree of membership for the pairs adding to z. The membership grade assigned to z, $\mu(A + B)(z)$, is the maximum possible membership value from the pairwise combination of x and y.]

Also, fuzzy multiplication is defined as

$$\mu_{A*B}(z) = [\max \{\mu_A(x) \min \mu_B(y)\}] \tag{2b}$$

For example, given A and B as

$$A = \text{low} = [0|1.0, 1|1.0, 2|0.6, 3|0.3, 4|0.1, 5|0.0, 6|0.0]$$

and

$$B = \text{medium} = [0|0.0, 1|0.0, 2|0.6, 3|1.0, 4|0.5, 5|0.2, 6|0.1]$$

then, applying Equations 2a and 2b,

$$A (+) B = [2|0.6, 3|1, 4|1, 5|0.6, 6|0.5, 7|0.3, 8|0.3, 9|0.1, 10|0.1, 11|0]$$

and

$$A (*) B = [0|1, 1|0, 2|0.6, 3|1.0, 4|0.6, 5|0.2, 6|0.6, \ldots, 36|0.0]$$

Figure 1 depicts the addition of fuzzy sets A and B. The use of hedges is another useful manipulation tool for modifying linguistic variables. One such factoring scheme is proposed by Zadeh for linguistic values (*20*). For example, given the following definitions for linguistic quantities large, medium, and small,

$$\text{Large} = [0.8|0.5, 0.9|0.9, 1|1.0]$$

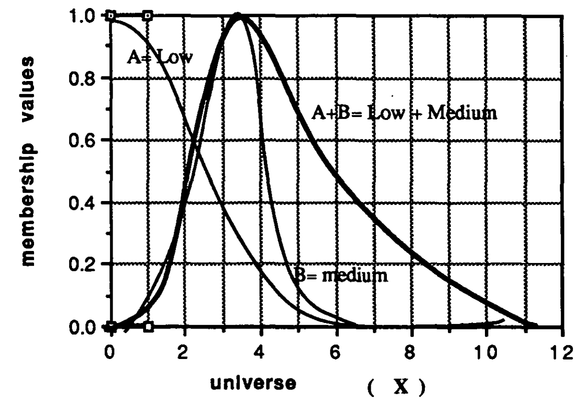

FIGURE 1 Illustration of fuzzy set addition of *A* and *B*.

Medium = [0.3|0.2, 0.4|0.8, 0.5|1.0, 0.6|0.8, 0.7|0.2]

Small = [0|1, 0.1|0.9, 0.2|0.5]

then very large, quite small, and very small can be defined as

Very large = $(\text{large})^2$ = [0.8|0.25, 0.9|0.81, 1|1.0],

Quite small = $(\text{small})^{5/4}$ = [0|1, 0.1|0.88, 0.2|0.42], and

Very small = $(\text{small})^2$ = [0|1, 0.1|0.81, 0.2|0.25].

Thus, using a similar factoring scheme, it is possible for an analyst to define different intensity for a given linguistic quantity.

FRAMEWORK FOR SERVICE SYSTEM LOS EVALUATION

The structure of the LOS evaluation proposed is depicted in Figure 2. The structure represents a hierarchical service system decomposed into its component service attributes, each of which can be associated with a linguistic variable name. Thus, at the highest level of the hierarchy is the node representing the overall LOS of the service system; the next level below indicates the service attributes at this level. Further decomposition of the service system can be represented at lower levels, depending on the size of the system being evaluated.

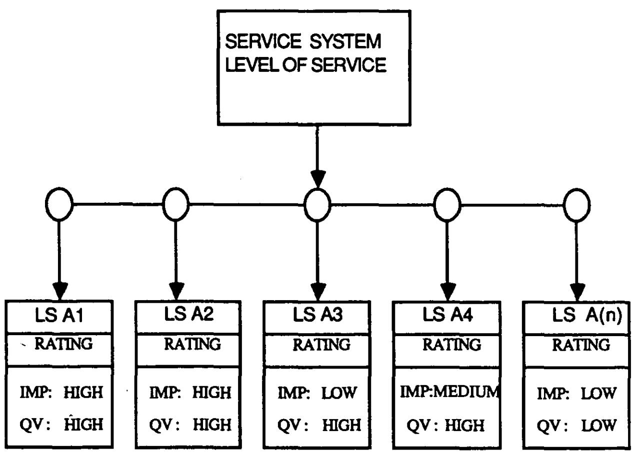

FIGURE 2 Schematic diagram depicting a service system.

For the design of the fuzzy LOS model, the existing service system initially must be evaluated by the users. At each system sublevel, information is required on the importance of each particular attribute to the evaluation of the service quality. In this approach, the values for the importance rating and quality of service are expressed as linguistic quantities, or fuzzy linguistic values. In Figure 2 a hypothetical evaluation is shown with attribute LS *A*1 evaluated as having an importance rating of high and a quality of service value of medium. These two quantities are the fuzzy values that define the linguistic variable LOS of LS *A*1.

The importance rating provides a fuzzy weight for each attribute, or LOS component LS(*i*). Weights or importance ratings can be determined using existing techniques, as given by Saaty (*11*), and other market research methods, such as conjoint analysis. A generalized tree structure to evaluate an airport service system is shown in Figure 3. A similar structure can be designed to evaluate airline and other transportation services. Before the service system evaluator is modeled, the the linguistic variables, fuzzy subset for each variable, and membership grade for each fuzzy term must be defined. For instance, the facility check-in can be assigned linguistic variables *check-in time* and *waiting time*, with both variables assigned three fuzzy subset values: acceptable, tolerable, and unacceptable. The universe of the fuzzy set then is defined on both the check-in time and waiting time on the time scale. The system analyst also has to provide, a priori, a membership function for each fuzzy value. This step is vital because the membership values give meaning to each fuzzy value; that is, membership values restrain the fuzzy values to the universe of discourse. Zimmerman (*12*) provides empirical research on membership functions and definitions. This application suggests that in the case of passengers, a membership grade can be obtained at any service component if there is a physical quantity that can be related to that component. In work by Mumayiz and Ashford (*4*), the obtained P-R models indicate the existence of possible membership grade for each of the three linguistic values used, that is, good, tolerable, and bad, over the universe of processing times for different service components within the terminal. A linguistic variable, such as check-in time LOS, can be conceptualized, and it is evaluated using the primary terms *good*, *tolerable*, and *bad*. A linguistic variable for time-based service can be defined for most processing activities (Figure 3) with a time scale as the universe of discourse. At holding facilities, suggested linguistic variables include *crowding*, *comfort*, *visual interest*, and *waiting time*, defined by using a time and space scale as the universe. At circulatory facilities, suggested linguistic variables include *walking distance*, *directness*, *signing*, and *ease of transiting*, also defined by using distance and time scale measures as the universe. Because there are many possible variables for defining LOS at a particular facility, the expert needs to establish if-then heuristic rules that relate the "if" conditions at a given facility with "then" consequences, that is, LOS at the facility. For instance, a simple rule for LOS at check-in processing can be expressed: if the check-in time is acceptable and the queue space is acceptable, then LOS at check-in is acceptable.

The computation of the overall system LOS can be achieved using a model proposed by Zadeh (*20*) (Equation 3), which enables the computation of fuzzy weighted means at each level of the service system. (An alternative method for aggregating fuzzy measures of LOS is the use of Sugeno's fuzzy integral. In a system with n attributes that have known LOS measures (h_i) and weights (w_i), the overall LOS of the system using fuzzy integral is defined as {max [min (h_i, w_i)]} (*21*).)

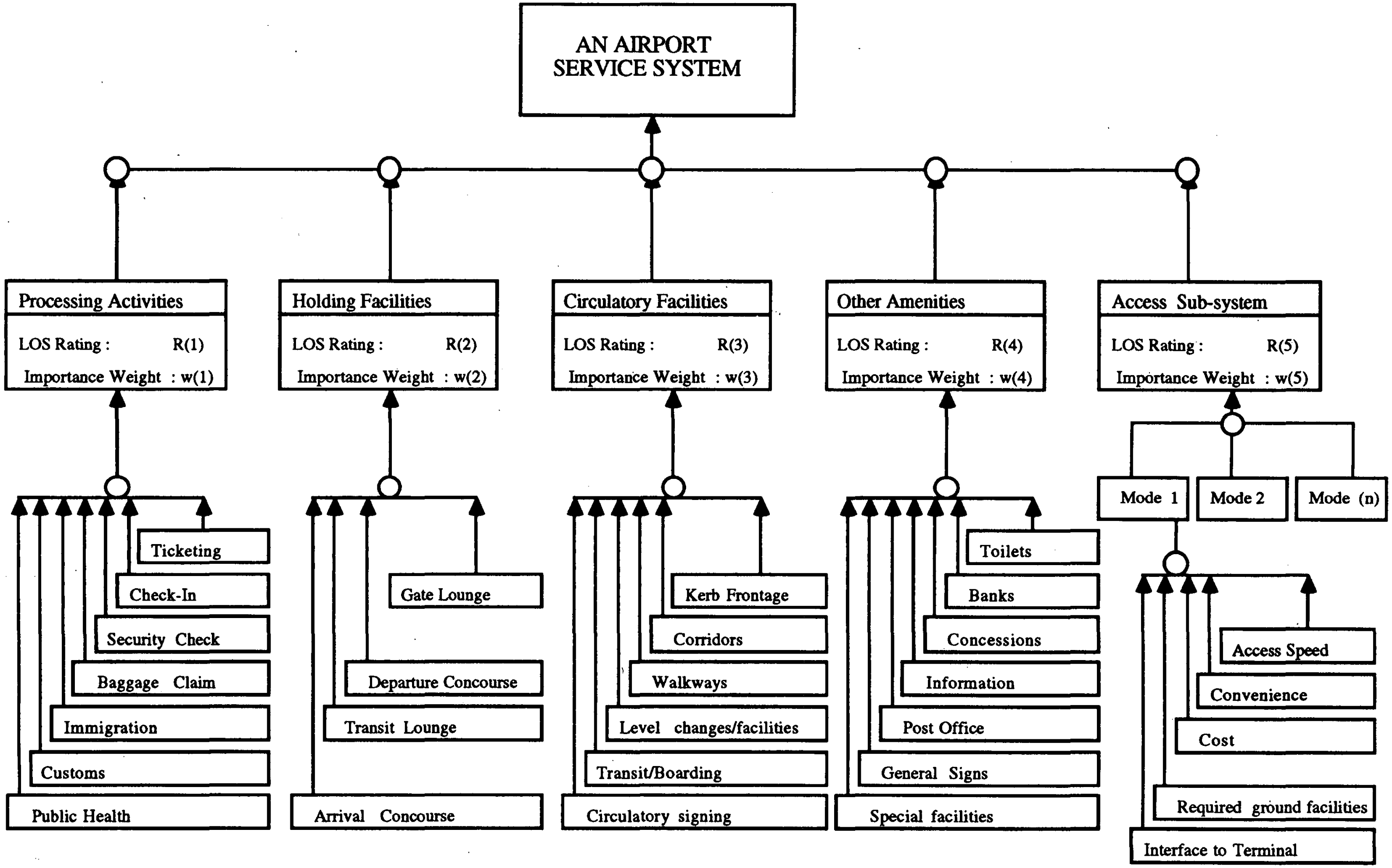

FIGURE 3 Airport service system.

Using this Equation 3, the overall LOS of the service system can be defined as a fuzzy mean Z:

$$Z_j = \sum_i^n \{[W_i] * [L_i]\} / \{\sum_i^n [W_i]\} \tag{3}$$

where

n = number of component i's at Level j,
$[W_i]$ = fuzzy weight, or importance factor, of component i at Level j, and
L_i = fuzzy quality of service component i at Level j.

The mean fuzzy set value also can be defined over m evaluators, or users of the service system. Having obtained a mean fuzzy value for the service system or its component, it is necessary to give a linguistic meaning to this value such that we can describe the system's overall LOS in words such as excellent or poor.

Linguistic Approximation of LOS Measures

It is required that the overall LOS definition of the service system be stated in natural language rather than fuzzy quantities. Thus, translating the obtained mean fuzzy value into its equivalent primary linguistic term is needed. Three main methods are provided in the literature: a measure of the Euclidean distance or best-fit method, successive approximation, and piecewise decomposition (*14*). The best-fit method is recommended when the number of the primary term set is small; when the primary term set is large the successive approximation method can be used. [The successive approximation method first assumes there are two close primary terms before various expressions are applied to these two points in order to approximate the closest natural language expression for the mean fuzzy value. The piecewise decomposition method, however, divides the linguistic variable into intervals. Each interval is combined with one of the standard logical connectors (e.g., *or* and *and*) to approximate the natural language expression.] Obtaining the approximate natural language expression is known as approximate reasoning or linguistic approximation. For this application, the best-fit approach is recommended. Given a fuzzy set Z, for which a natural language approximation will be computed later in this paper, and a known fuzzy set A representing one of the natural language expressions used for rating LOS, then the distance D between Z and A can be computed as follows:

$$D(Z, A) = \left(\sum_{i=1}^{k} \{ [\mu_Z(i) - \mu_A(i)]\}^2\right)^{0.5} \tag{4}$$

where

$D(Z,A)$ = Euclidean distance between fuzzy sets Z and A;
$\mu_Z(i)$, $\mu_A(i)$ = membership values for elements i of Z and i of A, respectively;
k = integer that defines the highest element in value in fuzzy sets of Z and A.

The calculation of Equation 4 is performed for all the expressions in rating natural language. The natural language expression that produces the shortest Euclidean distance from Z is taken to be the best fit to Z and is used as its natural language equivalent.

Application of Methodology

The proposed methodology is illustrated using a simplified application to evaluate processing services at an airport. The modeling procedure is summarized as follows:

1. Identify clearly and classify the service system as a decision tree (as in Figure 3), indicating the component of the system at each level and the appropriate linguistic variables that can be used to describe a particular facility.
2. Define the natural language fuzzy subset for each variable appropriate for defining the level of service for each component of the service system.
3. Define the universe of discourse (X) to be used to give values to the linguistic variable and also define the membership grade for each of the linguistic fuzzy values over the universe of discourse. Where hedges apply, define the factoring required to modify the primary terms using the defined hedge. A time/space measure can be used in the stated example.
4. Obtain an evaluation of the system from users or experts for all components of the system for which such an evaluation is stated, using one of the linguistic values already defined as well as an indication of the importance of each particular component to the overall LOS of the service system.
5. Determine the mean fuzzy value of the system, given Number 4 and translate the obtained fuzzy value into its approximate natural language expression.
6. Establish procedural rules for LOS system evaluation. The objective is to implement the rules into a computerized advisory system that can be simulated for different policy options as well as predict the LOS conditions within the terminal. A program in C can then be developed in order to implement both the fuzzy set computations and procedural rules, with graphic enhancement to the output, displaying the changing state of the service system and its component over time.

To illustrate the preceding methodology, a subsystem of Figure 3 is evaluated, that is, the processing activity subsystem for departures with just three components: check-in, security, and passport control. The final level of services at these components are assumed to be low, medium, or high without the heuristic rules, while the universe is defined as the set $\{0,1,2,3,4,5,6,7,8,9,10\}$. This set can be translated into timespace measures relating to the terminal, with a high set value associated with a high disutility in service quality. To ease the manual computation, the set is restricted to $\{0,1,2,3,4\}$. The following natural language expressions and corresponding fuzzy set values are defined for each of the processing activity components:

Check-in:

$$\begin{aligned}\text{Low} &= (Lc) = \{0|0.0,\ 1|0.1,\ 2|0.8,\ 3|1.0,\ 4|1.0\}\\ \text{Medium} &= (Mc) = \{0|0.0,\ 1|0.7,\ 2|1.0,\ 3|0.3,\ 4|0.0\}\\ \text{High} &= (Hc) = \{0|1.0,\ 1|0.5,\ 2|0.1,\ 3|0.0,\ 4|0.0\}\end{aligned} \tag{5}$$

Security:

$$\begin{aligned}\text{Low} &= (Ls) = \{0|0.0,\ 1|0.6,\ 2|1.0,\ 3|1.0,\ 4|1.0\}\\ \text{Medium} &= (Ms) = \{0|0.0,\ 1|1.0,\ 2|0.1,\ 3|0.0,\ 4|0.0\}\\ \text{High} &= (Hs) = \{0|1.0,\ 1|0.1,\ 2|0.0,\ 3|0.0,\ 4|0.0\}\end{aligned} \tag{6}$$

Passport:

$$\begin{aligned}\text{Low} &= (Lp) = \{0|0.0,\ 1|0.5,\ 2|1.0,\ 3|1.0,\ 4|1.0\}\\ \text{Medium} &= (Mp) = \{0|0.0,\ 1|1.0,\ 2|0.1,\ 3|0.0,\ 4|0.0\}\\ \text{High} &= (Hp) = \{0|1.0,\ 1|0.2,\ 2|0.1,\ 3|0.0,\ 4|0.0\}\end{aligned} \tag{7}$$

LOS at the processing activity node is defined a priori as

Processing activity node:

$$\text{Low} = (L\text{pa}) = \{0|0.0, 1|0.5, 2|1.0, 3|1.0, 4|1.0\}$$

$$\text{Medium} = (M\text{pa}) = \{0|0.0, 1|1.0, 2|0.1, 3|0.3, 4|0.0\}$$

$$\text{High} = (H\text{pa}) = \{0|1.0, 1|0.2, 2|0.1, 3|0.0, 4|0.0\} \quad (8)$$

Importance weights also need to be defined for the system. Typically for transport services, if an attribute or component is performing well, it is less likely to be perceived by its users as being important relative to other components, and vice versa. Thus, the importance level similarly should be defined as fuzzy quantities rather than as crisp weights. For this example, the fuzzy values for importance weight are defined as low (Li), medium (Mi), and high (Hi) where

$$Li = \{0|0, 1|0.0, 2|0.1, 3|0.5, 4|1.0\}$$

$$Mi = \{0|0, 1|0.1, 2|1.0, 3|0.1, 4|0.0\}$$

$$Hi = \{0|1, 1|0.5, 2|0.1, 3|0.0, 4|0.0\} \quad (9)$$

Assuming the components of the processing activities are evaluated in natural language as

LOS at check-in = low = Lc

Importance weight = Hi

LOS at security = high = Hs

Weight = Hi (9a)

LOS at passport control = medium = Mp

Weight = Li (9b)

Then the overall LOS associated with the subsystem can be computed using Equation 3 as

$$Z = \{Lc * Hi + Hs * Hi + Mp * Li\} / \{Hi + Hi + Li\} \quad (10)$$

Evaluating Equation 10 needs the application of fuzzy set addition, multiplication, and division as defined and illustrated earlier in the paper (Equations 1 and 2). $Lc * Hi$, $Hs * Hi$, $Mp * Li$, and $(Hi + Hi + Li)$ therefore are computed using Equations 5 through 9, as follows:

$$Lc * Hi = \{0|1.0, 1|0.0, 2|0.5, 3|0.5, 4|0.5, 5|0.1, 6|0.1, 7|0.1, 8|0.1, 9|0, 10|0\}$$

$$Hs * Hi = \{0|1.0, 1|0.1, 2|0.1, 3|0.0, 4|0.0, 5|0.0\}$$

$$Mp * Li = \{0|0.0, 1|0.0, 2|0.1, 3|0.5, 4|1.0, 5|0.5, 6|0.1, 7|0.1, 8|0.1, 9|0.0\}$$

$$(Hi + Hi + Li) = \{0|0.0, 1|0.0, 2|0.1, 3|0.5, 4|1.0, 5|0.5, 6|0.1, 7|0.1, 8|0.1, 9|0.1\}$$

Performing the division required in Equation 10, the obtained LOS of the processing activity subsystem is computed as

$$Z = \{0|0.0, 1|0.5, 2|0.5, 3|0.5, 4|0.1, 5|0.1, 6|0.1, 7|0.1, 8|0.1, 9|0.0\}$$

Z needs to be normalized by adjusting the degree of membership of its elements so that at least one element has a membership value of 1 in the set. [A fuzzy set is normalized by adjusting the degree of membership of the elements such that at least one element has the value of 1 in the set. The concept of convexity (also known as convex closure) means adjusting the membership values of a fuzzy set upward, if necessary, to ensure a relatively smooth curve so as to avoid any discontinuities in the fuzzy set function.] Furthermore, restricting the set in the interval {0,1,2,3,4}, Z normalized is

$$Z = \{0|0, 1|1.0, 2|1.0, 3|1.0, 4|0.2\}$$

Next, Z is translated into its approximate natural language equivalent. To accomplish this, Equations 4 and 8 are applied to find the shortest distance $D(Z, A)$ between Z and the primary terms Lpa, Mpa, and Hpa. Substituting membership values from Z and A into Equation 4,

$$D(Z, L\text{pa}) = \{(0-0)^2 + (1-0)^2 + (1-0.1)^2 + (1-0.5)^2 + (0.2-1)^2\}^{0.5} = 1.643$$

$$D(Z, M\text{pa}) = \{(0-0)^2 + (1-0.1)^2 + (1-1.0)^2 + (1-0.1)^2 + (0.2-0)^2\}^{0.5} = 1.288$$

$$D(Z, H\text{pa}) = \{(0-1)^2 + (1-0.5)^2 + (1-0.1)^2 + (1-0.0)^2 + (0.2-0)^2\}^{0.5} = 1.761$$

Thus, the natural language approximation to describe the observed LOS at the subsystem (i.e., processing activity subsystem) is medium. This approximation can be attributed to the low LOS given to check-in, which has a high importance rating. The approximate value of medium is also closer to low (Lpa) than Hpa. This fact implies that by using hedges, the approximate value of Z as determined can be refined such that $D(Z,A)$ is minimized further.

CONCLUSIONS

For most service industries, the need to meet the client's requirements satisfactorily is a key management objective to successful business. This objective requires regular assessment of LOS to ensure that high standards are maintained. A major requirement for any technique used is the need to measure the various attributes of the service system according to its effectiveness to meet customers' requirements satisfactorily. It is shown that existing methods of measuring LOS, particularly in air transport, have limitations in that each method attempts to provide a crisp value measure that does not translate easily to the subjective perception of the service system as seen by the user. It is also difficult to relate such weights to the original attributes of the service system.

The method proposed in this paper is the application of fuzzy set theory. This paper demonstrates how this theory can be applied to evaluate transport services using linguistic variable modeling. An advantage of developing such a system is that the modeling framework is more compatible with passengers' perceptions of the system or transport services through imprecise and vague linguistic values. Comfort and convenience are classic transport service attributes that have such subjective, imprecise meanings. Most passengers easily can express in linguistic terms their feelings on such qualitative service attributes without being able to provide a numeric assessment. The proposed methodology allows for modeling the linguistic variables provided by the users via fuzzy sets and linguistic value computation.

Although the approximate linguistic value of the airport service subsystem for the simplified illustration can be deduced, it can be seen that manual computation of the linguistic variable can be tedious. This task is made easier by the computerized implementation of the evaluation method. Such computerization can enhance the development of the methodology into an *expert* LOS assessment system, with better refinement of the service levels, including LOS graphics display capabilities. Further research therefore is needed to enhance the computerized methodology as well as research to establish the membership function for the various components and subsystems of a service system, such as an airport. The ability to report service level through users' perceptions is the major strength of this technique. The computerized model can be extended and applied to other transport problems involving multicriteria decision analysis. Once a fuzzy model of service perception has been defined, this model can be used for evaluating daily service quality. It also can be used for checking new system designs without the need to repeat the measurements of service preception.

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